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ASSUMPTION MEASUREMENT APPLICATIONS FOR THE INDIVIDUAL DECISION-MAKER

by

Jarrod W. Wilcox

February, 1971 509-71

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A B S T R A C T

Different people very often make different decisions in objectively similar situations because they use different attributes to characterize the situation. A previous paper by the author discussed a practical methodology for measuring these differences. This present paper describes and illustrates three general kinds of uses such measures have in helping an individual decision-maker engaged in broadly repetitive decision-making.

The examples are taken from a study of stock market participants.

I. Introduction

The purpose of this paper is to briefly describe three broad categories of application advances made possible through the introduction of an explicit measurement of the assumptions which underly broadly repetitive decisions.[1]

The specific methodology on which the discussion is based has been recently described in detail elsewhere. Some of the benefits of the applications to be described, however, could be realized using competitor measurement methodologies.[2]

In brief, the formal measurement of decision assumptions is useful because managers and decision-makers find it difficult to accurately describe their own assumptions in response to direct, informal questioning. One basic difficulty is that the dimensions used by the decision-maker to characterize the decision situation may be different than those of the questioner. A second problem is that one may not be consciously aware of the strength of influence of each different factor or dimension on his decision. The measurement of decision assumptions consists, then, of two parts. First, one elicits from the decision-maker through factor analytic or multidimensional scaling methods the dimensions he uses to characterize decision situations. Second, one relates statistically the positions of decision situations along these various attribute dimensions to their measured decision responses.

The author's method is based on a factor analysis of ratings of situations on scales elicited through a Role Repertory Test.[3]

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[1] Much of this paper is based on work described in the author's unpublished doctoral dissertation; see Wilcox [7].

[2] See Wilcox [8] for a description of this and competitor measurement methodologies.

[3] See Kelly [4].

This step is followed by pre-ordered step-wise regression of the factor scores thus obtained against an independently measured decision variable. Advantageous features which modify this method are:

1. decision-maker specification of the number of intervals into which each scale is to be divided before rating and factor analysis;
2. whenever inter-decision-maker comparison is desired, the use of two separate data sets, an individualized one for factor analysis of the scales and another one based on a common set of situations from which factor scores are to be derived for later regression analysis with the decision variable;
3. restriction of regression to factors previously tested as significant, and entry of these factors into the regression in descending order of eigenvalues;
4. conservative regression tests of significance whose degrees of freedom are based on all factors previously tried, even if some had been previously rejected.[4]

Applications of such measurements are varied. Of particular interest are those which a single decision-maker could use with limited resources and without undue disturbance of his organizational context:

1. simple revision of assumptions on the basis of decision outcome evidence;
2. improving the match between the flow of information given to or scanned by the decision-maker and that which actually influences his decision;

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[4]Example results for the three decision-makers used here are shown in the Appendix.

3. observing changes in his assumptions through time, with applications for both improved consistency and improved ability to sense changes in supporting information.

The application illustrations are based on data taken from the author's research on the assumptions of participants in the stock market regarding suitability of particular common stocks for the attainment of investment objectives.

II. Simple Revision of Assumptions Based on Decision Outcomes

Most decision-makers, when first confronted with a new type of decision, seem to quickly, if imperfectly, learn many of the important factors which bear on the decision's success. After a relatively few repetitions, however, decision-makers typically reach a capability plateau. They may remain capable of partially adapting in the face of environmental changes their appraisal of what is important. However, cumulative, pro-active learning often comes to a standstill. For example, in the author's previous study of participants in the stock market, many of the experienced trust officers and investors gave all the appearances of a stable, crystallized, if inexplicit, decision framework. Yet most of them appeared fully aware that there was potential for improvement. If the reader is not persuaded by such subjective observations, consider the following psychological arguments:

1. when decision outcomes are removed in time from the decision point, learning is made difficult by memory limitaions, particularly regarding rejected alternatives;
2. decision-makers notice and remember "evidence" presented by a single crisis much better than numerous small indications which are difficult to distinguish from background noise;

3. Self observation of one's own assumptions in making a decision is ordinarily imprecise and effortful;

4. Global, indefinite challenges to one's established viewpoint are more liable to be rejected than localized, specific ones.

For these reasons, a practical, explicit recording of assumptions and a test of them individually against the evidence of devision outcomes is highly desirable. The result will improve the decision-maker's ability to sustain the learning process beyond the mentally comfortable plateau at which, unaided, he would tend to remain.

Typical data taken from the larger study in which the measurement methodology was tested are used to illustrate how it could be used for this purpose.

Of the twenty-five in the larger study, three stock market participants who had indicated that their investment goals were short-term capital gain were selected to illustrate this possibility.

Decision-maker Participant	Type	Assumption Measurement Date	Outcome Checking Date
07	professional trader	Sept. 5, 1969	December 1, 1969
22	individual investor	July 29, 1969	December 1, 1969
38	large fund portfolio manager	August 4,1969	December 1, 1969

Table 1

Factor scores derived from the participant's ratings of nineteen stocks along various attribute scales were calculated.[5]

[5]There were twenty stocks used in the larger study. One of the stocks was not traded on the exchange throughout the period needed for data here.

The participant's direct ratings of the stocks on suitability for investment scales and on various other attribute scales were measured based on data taken at the "assumption date" in the table above. Actual performance of the nineteen stocks was measured in terms of the natural logarithm of the ratio of the stock price at the "outcome checking date" to that of the assumption date.[6] The reader is here invited to turn his attention to the Appendix, which presents the pertinent factor structures, stocks utilized, and assumption measures for these decision-makers.

One might question whether these decision-makers were utilizing optimally the information already available to them for rating stocks according to their investment objectives. With respect to the stock market, of particular relevance is the question of whether or not relevant attributes for making better than random investment ratings are at all available. Answers to these questions may be gotten, if the evidence is strong enough be rejected as small-sample statistical noise, through the approach illustrated. Actual stock price performance data (Y^*) were correlated with each participant's summary preference or suitability rating (Y) for each stock and also regressed against underlying-attribute factor measures (F_k). The Y and F_k had previously been related to get the assumption measures. For each subject, coincidentally, there were four factors previously tested as significant. For each decision-maker these significant factor scores were forced into a separate stepwise regression. For the purposes of this research, the order of entry was pre-specified. Factors with the largest eigenvalues were entered into the regression equation first.

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[6]The data were adjusted for stock splits but not for dividends.

The following best linear regressions were obtained. The coefficients will be more meaningful if reference is made to the Appendix, where sample means and standard deviations of measurements of the Y and F_k variables are given.

Standard errors are given in brackets below the coefficients.

Decision-maker	Regression
07:	$Y^*_{07} = 0.02765 + (-0.00054)F_{07-2}$ [0.00044] $R^2 = .0797$, $F_{1,17} = 1.473$, Not significant
22:	$Y^*_{22} = 0.52210 + (-0.00089)F_{22-2} + (-0.00061)F_{22-3}$ [0.00029] [0.00022] $R^2 = .4384$, $F_{2,16} = 6.246$, Significant at .025 level.
38:	$Y^*_{38} = -0.14166 + (-0.00023)\ F_{38-1} + (-0.00079)F_{38-2}$ [0.00064] [0.00029] $R^2 = .3190$, $F_{2,16} = 3.748$, Significant at .05 level.

Note: the significance level figures make the usual normality assumptions.

Table 2

Thus, there is some evidence that information was available through the factors to Decision-makers 22 and 38 which might potentially be useful.

Also, if we look at the actual assumed suitability ratings, Y, we find that one of the correlations, that of the large fund portfolio manager, is fairly large, though not really very statistically significant.[7]

corr. $(Y_{07}, Y^*_{07}) = .278$, $R^2 = .077$

corr. $(Y_{22}, Y^*_{22}) = .071$, $R^2 = .005$

corr. $(Y_{38}, Y^*_{38}) = .462$ $R^2 = .213$

Table 3

Unfortunately for purposes of simple illustration, these results are deceptive. The statistical tests assume independence of observations. In fact, we know that returns to individual stocks are highly inter-correlated with the performance of the market as a whole. About all we can say from these statistics is that there are indications that Y_{38}, F_{22-2}, F_{22-3}, and F_{38-2} have either face validity as predictors of differential stock performance or else that they appear predictors of differential performance given a valid prediction of the direction of the market as a whole. Since "stock volatility" would satisfy the latter requirement, and this construct is already well known, the foregoing results are not very useful.

However, if we partial out the variance associated with that of the market as a whole, we can base the regression on what are much more nearly independent observations. To do this, the closing prices on the first trading day of each month from January 1967 through June 1969 were recorded for each of the nineteen stocks and for the Dow-Jones Industrial Average. For each stock the natural logarithm of month-to-month price ratios, adjusted for stock-splits (though not for dividends) was regressed as a simple linear

[7] It would have appeared more significant if it had not been tested simultaneously with those of two other decision-makers.

function of the same series for the Dow-Jones Industrial Average. The equation thus obtained for each stock gave a measure of the expected variance explainable by the action of the market as a whole.[8] This equation was used to partial out from the actual outcome data the variance to be expected from market movement on the basis of this model. The residuals which remained appear to be the actual outcome data unexplained by the market factor.

Systematic inter-correlation due to industry factors appears negligible in this set of observations, but could also have been partialled out as a further refinement. Let us label these residual outcomes Y'. Following the same pre-specified step-wise regression procedure as before, the following best estimates were obtained, very similar to the earlier ones.

Decision-maker

07: $Y_{07} = 0.03306 + (-0.00065)F_{07-2}$

[0.00045]

$R^2 = .1101$, $F_{1,17} = 2.103$, Significant at the 0.20 level

22: $Y_{22} = 0.45633 + (-0.00086)F_{22-2} + (-0.00053)F_{22-3}$

[0.00029] [0.00021]

$R^2 = .4097$, $F_{2,16} = 5.553$, Significant at the 0.05 level

38: $Y_{38} = -0.13002 + (-0.00023)F_{38-1} + (-0.00076)F_{38-2}$

[0.00066] [0.00030]

$R^2 = .2890$, $F_{2,16} = 3.251$, Significant at the 0.10 level

Table 4

[8] The regression coefficient is a measure of the now famous "β" of modern portfolio theory; see Sharpe [5] and Jenssen [3].

Thus, there is some evidence that each of the decision-makers, particularly Decision-maker 22, had access to information measured through the F_k's potentially useful in rating the stocks, and not dependent in a linear fashion on a prediction of the market as a whole.[9]

Parenthetically, though this result is merely a by-product of the present research, it has not only immediate practical implications for stock market participants, but also for the theory of capital markets. The statistical significance reported is subject to modification pending further investigation of:

1. a check of the normality assumption;
2. a check to see if regression coefficients with the Dow-Jones derived from quarterly data are different enough from those from monthly data to affect the results, and if so, whether the difference is unfavorable;
3. a check to see if the regression coefficients were out of date because of their evolution through time since the period from which they were derived, and if so, whether the difference is unfavorable.

The theoretical import is not really a challenge to the market price random walk hypothesis: There is no good evidence that the Y (suitability ratings) are good predictors. However, the results here do give rise to some suspicions regarding the "thinness" of the participant assumption framework within which profit opportunities are competed away. That is, the market is relatively perfect given the existing state of distribution of participant assumptions; the present results indicate something abouth how "far" assumptions need to be changed by an individual to create local imperfections, profit opportunities, in the market. They also indicate that

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*However, the lack of difference in the regression equations for Y^* and Y' indicates the need to interpret these data cautiously.

such imperfections can be created by changes in assumptions, that is, in models, as opposed to mere changes in data.

Putting aside this interesting detour, let us return to the general application. In our illustration, the next question is whether the decision-makers actually use this information in making their ratings. If we look at the suitability ratings, Y, we find

corr. $(Y'_{07}, Y_{07}) = 0.408$,	$R^2 = 0.1665$ Significant at 0.10 level
corr. $(Y'_{22}, Y_{22}) = 0.040$,	$R^2 = .0016$ Not significant
corr. $(Y'_{38}, Y_{38}) = 0.441$	$R^2 = .1945$ Significant at 0.10 level.

Table 5

Thus, it appears possible that Decision-makers 07 and 38 are using a greater degree of valid information than that measured through the factor attributes F_k obtained in the larger study. It is, however, quite likely that Decision-maker 22 is mis-using (using a lesser degree of) this information potentially available to him. In the larger study, the following was obtained as a measure of his assumptions:

$$Y_{22} = 2873 + (-1.94)F_{22-1} + (-2.93)F_{22-3} + (-1.54)F_{22-6}$$

In fact, he placed reliance not only on F_{22-3}, which our evidence indicates was helpful, but also on F_{22-1} and F_{22-6}, which were not, and ignored F_{22-2}, which our evidences indicates would have been quite useful. There is even evidence that he placed the wrong sign on F_{22-1}, since regression of actual outcome data gave:

$$Y'_{22} = 0.30883 + (0.00057)F_{22-1}$$
$$[0.00034]$$
$$+ (-0.00085)F_{22-2} + (-0.00012)F_{22-3}$$

As a sidelight, Decision-maker 22 in his interview in the larger study had contrasted what he felt to be his past dependence on "fundamental" analysis with his present reliance on "technical" or "chartist" analysis; this would correspond to a shift from F_2 to reliance on F_3. In the practical use of the presently proposed application of measured assumption data, the evidence presented should act as a signal to him that he ought to consider the greater use of his presently underutilized "fundamental" analysis.

This kind of evidence or learning information could be beneficially used by the decision-maker to revise or confirm his implicit assumptions; it could also be used to revise an explicit model of his assumptions such as those which were estimated in the larger study on which this is based.

Thus, for example, the models earlier obtained by the assumption measurement were the following:

$$Y_{07} = 523.0 + (-3.110)F_{7-2}$$

$$Y_{22} = 2872.8 + (-1.941)F_{22-1} + (-2.926)F_{22-3} + (-1.542)F_{22-6}$$

$$Y_{38} = 347.7 + (0.989)F_{38-1} + (-1.292)F_{38-2}$$

Table 6

Such models could be maintained by the decision-maker as a kind of back-up check device against which his actual utilization of his existing subjective knowledge could be compared. The learning information represented through the preceding evidence could be applied to these models to change the co-

efficients by which each factor is weighted to arrive at a decision. In this manner the already-estimated models of the manager's existing assumptions could "learn" on the basis of the new evidence. Various strategies for incorporating learning information into the models could be used. One of the simplest and probably most useful would be to estimate the "best" predictor equation with actual consequence data, in this case, the actual percentage price changes, and to make incremental adjustments of the prior existing model toward the newly-estimated "best" predictor equation with each new set of actual consequence data.

That is, let

$$Y_t = b_o + b_1F_1 + b_2F_2 + \ldots b_mF_m$$

be the existing assumption at time t. Let

$$Y = b_o + b_1F_1 + b_2F_2 + \ldots b_mF_m$$

be the "best" model from the new data set or learning situation. Then let:

$$Y_{t+1} = Y_t + \frac{b_o' - b_o}{\gamma_o} + \frac{b_1' - b_1}{\gamma_1} F_1 + \ldots \frac{b_m' - b_m}{\gamma_m} F_m$$

where γ_k, k = 1, m, is a number greater than unity which governs the sensitivity of the model to new learning information along various F_k.

The foregoing learning procedure is not suggested as optimal in a maximum liklihood sense; it is merely suggested as a simple example of what might fruitfully be used by practical decision-makers.[10]

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[10] Non-linear and interactive terms among the F_k, k = 1, m, could also be used; see Slovic [6].

The evidence presented illustrates the use of measured assumptions in learning based on decision outcomes. This is our major purpose here. Though the example from the stock market is certainly intriguing, it serves mainly as an indication of potential in less difficult areas.

III. Use of Measured Assumptions as a Guide to Information Search

The pertinent information for current decision-making will generally be data relating to the attributes which figure most heavily in the factors assumed by the decision-maker to be important.

Suppose the decision-maker is not aware in detail of the information utilization he makes in coming to a decision; this is typically the case in reality. Models of assumptions such as those given on page 11 for each decision-maker can provide an indication of the decision-maker's information utilization. For example, in the case of Decision-maker 38, we have, based on a very limited sample of twenty stocks,

$$Y_{38} = 347.7 + (0.989)F_{38-1} + (-1.292)F_{38-2} \ .$$

It should be noted that the complexity of this model could very well be greater if it were based on a larger sample size. The factor measures F_{38-1} and F_{38-2} are based on the factor structure shown in the following table. The poles at the left represent a high score for the factor, those at the right a low value.

Used and Potentiall Useful Attribute Information, Decision-maker 38

Factor I (F_{38-1})

.88 stock has appreciated a great deal recently	stock has declined a great deal recently
.97 is a very fashionable stock at present	presently in market disfavor
.87 not so	viewed as a conglomerate
.95 made new highs for the year very recently	closer to its lows than its highs for the year

Factor II (F_{38-2})

.91 so vast it's beyond comprehension, predictable	not so
.91 stock price based on dividends	not so
.76 company less aggressively managing its assets than in the past	company more aggressively managing its assets than in the past
.74 old style, sleepy	not so

Table 7

Based on the evidence regarding regressions with residual stock price change outcome data as presented in the last section, F_{38-2} has only weak evidence of being useful, and F_{38-1} is no apparent help at all. As an alternative or supplement to assumption revision, Decision-maker 38 might investigate the adequacy of the information on an individual stock's position along various attribute scales which he is given by his staff or through

his own search.

It has been suggested by the author's previous research that there are major differences between decision-makers not only in their assumptions about particular stocks, but also in their assumptions as to which attributes should be used to characterize stocks in order to select among stocks those best suited to attain some investment objective. Our analysis has been focused entirely on the second type of assumption -- on which attributes of stocks are means to an investment end. However, once these latter are measured, it becomes more fruitful to examine the first type. To what degree does a particular stock possess some attribute?

In this context, we may examine attributes underlying Decision-maker 38's F_{38-1} and F_{38-2}, on which he appears to rely. How good is the decision-maker's state of information regarding the position of the various stocks along those factors? For example, F_{38-1} is loaded heavily on:

"is a very fashionable stock at present" ---------- "presently in market disfavor."

Knowing the importance of this factor and this contributory raw attribute in his decision, Decision-maker 38 is now in a better position to seek additional raw attribute measures which can contribute to this factor, or to seek improved accuracy along the existing raw data attributes which have heavy loadings, such as the one shown above. Thus, as a result of our analysis, he might well make, for example, a greater effort to collect improved information relevant to deciding whether a stock was "fashionable" or not. In general, this would be an appropriate context in which to decide what information should be furnished to him by organizational information

systems such as the accounting system or, in this case, by the security analyst. As a further heuristic, since there is a little evidence F_{38-2} has greater real predictive value, more emphasis might be placed on data relevant to it rather than on F_{38-1}. In particular, use of security analysts or personal visits might be directed toward paying particular attention to F_{38-2} attributes, like changes in "management's aggressiveness in managing its assets", in order to further exploit the apparent predictive value of F_{38-2}.

The points made in the foregoing paragraph apply with equal force not only to attributes associated with factors actually used by the decision-maker but also to attributes associated with any presently non-used factors indicated as potentially predictive of actual price changes.

The foregoing type of application of the measurement of decision assumptions could be utilized in a variety of fields to examine the usefulness of existing organizational, staff, and individualized information support. Whenever it is being determined that information provided does not match the decision-maker's types of relevant and usable attributes for characterising decision alternatives, there are two choices:

1. change the information supply,
2. change the decision assumptions.

Both choices, improving intelligence information and educating the decision-maker, critically depend on effective identification of the used and non-used information. The application of the measurement of assumptions noted here appears to represent substantial progress in capability for such identification.

IV. Observation of Changes in Managerial Assumptions

Two basic kinds of usage by the individual decision-maker of the measurement of assumptions have been discussed. A third fundamental use consists of self-observation of changes over time of one's cognitive image of decision situations and of changes in assumptions about their implications. In this investigator's view, a decision-maker might very valuably look for such changes, seeking an explanation for those which he finds both significant and surprising. Easily available applications in this area include explicit measurement of changes in the decision-maker's assumptions as to appropriate characterizing attributes, with respect to:

1. consistency,
2. learning trends,
3. responses to shifts in the contextual environment,
4. responses to shifts in attribute information availability.[11]

Also available are applications measuring the much more frequent changes in assumptions as to a particular situation's attribute positions; in this case these correspond to changes in factor measure scores for a particular stock.

Decision-maker 22 is used as a simple example of the application of assumption measures to observing changes. We can analyze some basic aspects of his changes over time simply by constructing the correlation matrix of his factor measures and summary preferences or suitability ratings at two

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[11] Some operations researchers have gathered evidence that consistent decisions provide superior average performance; see Bowman [2]. One could investigate the available data used in this study to determine whether as predictors of actual outcomes the predicted suitability ratings as a function of the measured assumptions were superior to the actual suitability ratings.

points in time, and subtracting one from the other. In the larger study on which this is based, data was gathered regarding assumptions and then tested in a new data set several months later. Subtracting the correlation matrix in the first data set of the factor scores (F_k) and the suitability rating (Y) from the correlation matrix derived from the second data set, filled out by the decision-maker several months later, we get:

Table 8: Shifts in Correlations Among Significant Factors and Preferences

Subject 22

$\bar{\bar{R}}_{t+1} - \bar{\bar{R}}_t$ | Comment

	F_{22-1}	F_{22-2}	F_{22-3}	F_{22-6}	Y_{22}	Y_{t+1}	Y_t
F_{22-1}	.00	.12	.33	-.51	-.36	-.26	.10
F_{22-2}		.00	.18	-.29	.70	-.88	-.18
F_{22-3}			.00	.49	.43	-.05	-.48
F_{22-6}				.00	-.07	.21	.28
Y_{22}					.00	1.00	1.00

The statistical significance of such shifts is a very complicated function of the true population correlation matrix.[12] However, at the place of maximum expected sample variance, where the population simple correlations are zero, the complicated distribution simplifies, so that for sample size

[12] See Anderson [1].

N (here N = 20), and for simple pairwise correlations, R, the statistic

$$\frac{R^2/1}{(1-R^2)/(N-2)},$$

is distributed as Fisher's $F_{1, N-2}$ for a normal multivariate population. Here, a shift in R greater than 0.43 is significant at the 5 per cent level. If the population R is not equal to zero, shifts of this magnitude would be of somewhat greater significance.

In this case, the evidence indicates, among the "significant" factors, a strong increase in reliance on F_2 and a decrease in F_3 in coming to the preference Y. The meaning of such strong shifts will typically be explicable to the decision-maker. For example, Decision-maker 22 informed the investigator without knowing of these results that a temporary lack of currency in the "technical" stock information available to him for the second data set might have invalidated these data with respect to the model resulting from the first data set. The foregoing report of shifts clearly indicates this important event, as can be seen in the positive poles of F_{22-2} and F_{22-3}, shown as follows.

Table 9: Positive Poles of Factors Whose Usage Had Shifted, Decision-maker 22

Factor II

.83 demand for final use products indicates lack of growth

.88 serves consumer market

.82 decline in earnings

.77 fortunes tied to factors beyond company's control

.75 past performance has been worse than expected

.71 in highly competitive business where they are non-unique

Factor III

.85 short-term technical demand is weak

.76 long-term technical demand is worsening

.76 short-term technical demand is worsening

.82 stock price has recently moved down by a large percentage

This kind of data on shifting assumptions would be of somewhat greater usefulness if several, rather than just two, measuring points in time had been taken; in that case, one could more easily distinguish "steady-state" decision-maker inconsistency over time from other kinds of operationally significant changes in assumptions.

The usefulness of this kind of signal as to probable changes in information flow could be expected to be greatest when the decision process was informal and inexplicit.

V. Conclusion

Two kinds of interesting results have been presented here. First, the measured assumptions resulting from the application of the author's methodology appear to have practical use for the individual decision-maker

1. assumption revision based on outcome data;
2. guiding information search;
3. monitoring assumption changes and inconsistency.

Second, more or less as a by-product, we have obtained indications of the existence of potential local imperfections, or profit opportunities, in the stock markets. This latter finding, however, should be regarded with caution pending further study.

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A P P E N D I X

I. Common Stocks Used for Assumption Measures

1. Anaconda
2. American Motors
3. City Investing
4. Brunswick
5. Delta Air Lines
6. Four Seasons Nursing Center*
7. Fairchild Camera
8. Dymo Industries
9. International Telegraph and Telephone
10. General Electric
11. Monsanto
12. Loew's Theatre's
13. Pacific Petroleum
14. Magnavox
15. Standard Oil of New Jersey
16. RCA
17. American Machine & Foundry
18. Sperry Rand
19. Varian Associates
20. United Aircraft

*This stock was omitted in the comparison with actual outcomes because of data gathering difficulty.

II. Factor Structures of Significant Factors.

Only loadings with attribute scale ratings greater than 0.70 are shown here. The relative importance of a factor can be roughly judged by dividing its eigenvalue, E ,by the total number of attribute scales rated by the decision-maker, NV. This gives the proportion of the total normalized variance of attribute ratings explained by the factor.

The left pole of each factor represents a high factor score, the right pole a low score. The reader is reminded that the factor loadings represent the correlation of the factor scores with the attribute scale ratings.

Decision-maker 07: NV = 30

Factor 07-1 E = 5.2

.89	not so	research and development oriented
.87	profit growth probably the result of many favorable factors	one or two internal factors that would dramatically affect profits
.84	not so	would buy for technological reasons
.83	"out" of vogue	in vogue

Factor 07-2, E = 5.4

.72	large capitalization	small capitalization
.81	high trading volume	low trading volume
.72	stock not likely to ever be in or "out" of vogue	stock subject to sharp changes depending on whether it's in or "out" of vogue
.71	not so	company's product an existing or emerging necessity for a large market
.90	interest is mainly local around geographical area of company	widespread and active interest
.89	not so	could anticipate under certain circumstances large volume

Factor 07-3, E = 4.0

.89	take-over candidate	not so
.78	not so	price takes wide swings

Factor 07-5, E = 3.6

.87	trading vehicle, always some buyers and sellers	one-way stock -- everyone is selling or everyone is buying
.75	would take large volume to move price far	can move tremendously on very small volume

Decision-maker 22: NV = 34

Factor 22-1, E = 4.9

.80	highly speculative	not so
.88	low quality	high quality
.78	not so	considerable institutional participation
.84	thin market	has broad ownership

Factor 22-2, E = 6.8

.82	not so	growth oriented issue
.83	demand for final-use products indicates lack of growth	demand for final-use products indicates favorable growth
.88	serves a consumer market	serves a far from end-use market
.82	decline in earnings has occurred	high earnings growth has occurred
.77	fortunes tied to factors beyond company's control	not so, research oriented
.75	past performance has been worse than expected	past performance has been better than expected
.71	in highly competitive business where they are non-unique	in highly specialized market

Factor 22-3, E = 5.6

.85	short-term technical demand is weak	short-term technical demand is strong
.76	long-term technical demand is worsening	long-term technical demand is improving
.76	short-term technical demand is worsening	short-term technical demand is improving
.82	stock price has recently moved down by a large percentage	stock price has recently moved up by a large percentage

Factor 22-6, E = 3.5

.79	has a track record	has no track record
.86	listed on a major exchange	over the counter
.73	[not a recent issue]	recent issue

Decision-maker 38: NV = 40

Factor 38-1, E = 7.5

.88	stock has appreciated a great deal recently	stock has declined a great deal recently
.74	we have been successful in	we have been unsuccessful in
.97	is a very fashionable stock at present	presently in market disfavor
.87	not so	viewed as a conglomerate
.95	made new highs for the year very recently	closer to its lows than its highs for the year
.94	attitudes have <u>not</u> hardened against it	attitudes have hardened against it
.74	not so	cash heavy

Factor 38-2, E = 5.3

.91	so vast it's beyond comprehension, predictable	not so
.91	stock price based on dividends	not so
.76	company less aggressively managing its assets than in the past	company more aggressively managing its assets than in the past
.74	old style, sleepy	not so

Factor 38-4, E = 4.7

.90	not so	a real-estate play
.86	not so	a leisure-time, recreation stock
.72	presently losing money	presently very profitable

Factor 38-5, E = 3.3

.97	high multiple, high technology stock	not so
.97	open-ended growth potential	growth has some delimiting factor

III. Means and Standard Deviations of Y's and F_k's

These figures apply to the sample of nineteen stocks

Variable	Mean	Standard Deviation
Y_{07}	469.5	284.9
F_{07-1}	320.0	92.0
F_{07-2}	15.3	65.5
F_{07-4}	-479.9	79.6
F_{07-5}	671.7	242.4

Variable	Mean	Standard Deviation
Y_{22}	457.9	325.4
F_{22-1}	-205.3	139.2
F_{22-2}	68.0	114.0
F_{22-3}	639.5	155.5
F_{22-6}	-34.6	67.7
Y_{38}	473.7	303.8
F_{38-1}	-94.3	46.5
F_{38-2}	-168.7	101.3
F_{38-4}	351.5	51.3
F_{38-5}	-83.3	126.7